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A Real-time Falls Detection System for Elderly

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***Abstract*— A real-time fall detection system is proposed to distinguish various falls during daily activities. Falls are detected in two steps: first a hierarchical algorithm is used to classify the motion and motionless postures such as lying, sit-tilted, sit-upright, standing and walking; it then analyzes whether the current lying or sit-tilted postures are normal or abnormal, based on posture transition and users' current position. If an abnormal lying or sit-tilted posture is determined, a fall alert will be delivered immediately; if a possible fall is raised (such as normal lying but on the ground), then a music based alert starts playing, and a fall or normal lying will be determined according to whether the user stops the alert music. The advantages of the approach are that it can distinguish various falls efficiently (in real-time within a smart phone), and can also significantly improve the "true positives" for the slow falls with a sit-tilted posture, as well as the "true negatives" for the normal lying compared to the existed fall detection algorithms.**

Keywords- fall detection; position; posture classification; posture transition; smart phone.

I. INTRODUCTION

Falls impact negatively on health and may be considered a major global problem, particularly for the elderly population and those who are suffering from a form of chronic disease. For example, people with chronic heart failure or stroke may suffer cardiac and/or gait disorders leading to the increased risk of falling during the daily activities. The world health organization (WHO) estimated that 424,000 fatal falls occur each year, making it the second leading cause of accidental deaths, resulting in huge financial implications worldwide. Elderly people have the highest risk of fatal falls. For example, more than 32% of older persons have experienced a fall at least once a year with 24% encountering serious injuries [1][2]. Falls are responsible for approximately 70% of accidental death in persons aged over 75. Approximately 3% of all persons who experience a fall will remain on the ground or floor for more than 20 minutes prior to receiving assistance [3]. The period of time spent immobile often affects their health outcome such as dehydration and hypothermia are some complications that may result. Getting timely help after a debilitating fall improves the chance of survival by 80% and increases the possibility of a return to independent living. Reliable and immediate detection of the fall is therefore important to ensure that the person may receive assistance as necessary. People who have experienced a fall may exhibit increased fear, depression or anxiety, which will decrease their self-confidence and motivation for independence and even possibly for remaining in their own homes. Therefore, an efficient fall detection system can assist elderly people living alone at home and potentially improve their life quality. This research documents a daily activity monitoring system that can be used to distinguish falls from other daily activities and deliver an alert in real time.

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The remainder of the paper is organized as follows. The related work is discussed in Section II. Methodologies for the system configuration and fall detection algorithms are described in Section III. The falls in various situations used to evaluate the fall detection algorithm and the experimental results are presented in Section IV. Finally, Section V focuses on the Discussion, Conclusion and the Future Work.

II. RELATED WORK

Different devices (such as environment-embedded sensors and wearable sensors) have been used to distinguish fall detection from normal daily activities. Sensors, e.g. cameras, can be embedded in a tracking environment; however, they can only monitor fixed places and there are privacy-protection problems. Wearable sensors such as accelerometers and tilt sensors are more flexible, allowing users to be monitored both within and outside of their home environment [4].

Falls are normally characterized by a large acceleration change compared to the types of measurements associated with normal daily living. Hence accelerometers are the most common device used for fall detection along with daily activity classification. For example, Kangas et al. [5] proposed a falls detection application based on accelerometers attached to the waist, wrist and head. Their experimental results demonstrated that measurements from the waist and head were more useful for the purposes of fall detection. Luo & Hu [6] introduced a two thresholds (acceleration amplitude and acceleration direction angle) based approach for fall detection using a waist-mounted accelerometer. Their algorithm obtained 100% accuracy for 'intentional' falls. Nevertheless, the approach did not successfully detect the situation where the subject lay down 'slowly'. Lindemann et al. [7] combined three thresholds (acceleration in the xy-plane and in 3-axes, in addition to velocity in 3-axes) to distinguish falls using two head-worn accelerometers placed orthogonally on the head behind the ears. Their head-worn accelerometers can offer sensitive impact detection for heavy falls. Nevertheless, such an approach is limited by its usability and user acceptance.

Some studies have combined accelerometers with other sensors to improve the reliability of fall detection. For example, Hwang et al. [8] introduced a three thresholds based algorithm for falls detection, using integrated accelerometer, gyroscope and tilt sensors, with a Bluetooth module for signals transmission. Their accuracy of fall detection was 96.7%.

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However, the range of users activities was limited only in the indoor. Bianchi et al. [9] used a heuristically trained decision tree to classify simulated falls based on integrated accelerometer with a barometric pressure sensor. Their experimental results demonstrated that the fall detection accuracy was considerably improved by using the barometric pressure sensor assisted system in comparison to using accelerometer data alone (96.9% vs. 85.3%), nevertheless, their decision tree algorithm was evaluated offline.

In this work, a real-time algorithm is proposed to detect various falls situation based on posture classification and posture transition analysis.

III. METHODOLOGY

The fall detection algorithm was developed and evaluated within a HTC (Android based) smart phone in real-time, based on data acquired from the phone's accelerometer and orientation sensors.

A. *System Configuration*

An HTC smart phone was used for data sensing and processing in this study. The phone embedded BMA150 3D accelerometer, orientation sensor, 3D Magnetic sensor, GPS and Wi-Fi. The phone's processor operates at 600MHz, the memory capacity is 512MB with an additional 2GB memory card and the operating system is Android version 2.3.3.

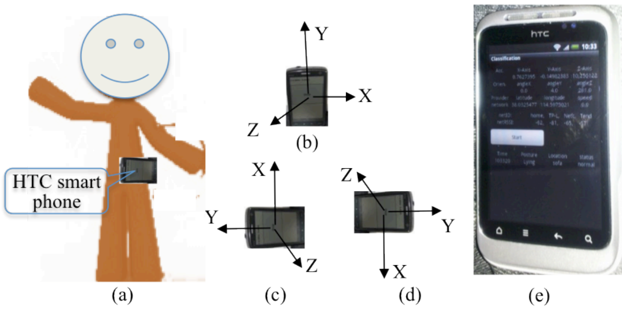

Figure 1. System configuration; (a) the phone is belt-worn horizontally on the left side of the waist; (b) *Y*-axis up if the phone is vertical; (c) & (d) *X*-axis up/down if the phone is horizontal and facing backward/frontward. (e) the interface of system on the phone.

The phone is belt-worn on the left side of the waist in a horizontal orientation as shown in Fig.1 (a). The sensor coordinate system is defined relative to the phone's screen as shown in Fig.1 (b), (c) and (d). The system interface on the phone is shown in Fig.1 (e).

B. *The Sampling Frequency Setting*

A study by Zhang et al. [10] has compared the activity classification accuracy based on data collected from the GENEA accelerometer, with the sampling frequency ranging from 5Hz to 80 Hz for the four types of activities: sedentary, household, walking and running. Their experimental results illustrated that the classification accuracy did not change significantly for sampling rates down to 5Hz; 80Hz (96.9%±1%), 40Hz (97.4% ± 0.7%), 20Hz (96.9%±1.1%), 10Hz (97%±1%) and 5Hz (95%±1.4%).

Lower sampling rates result in a lower data load and higher efficiency of data processing. Therefore, the sampling frequency was set at 5Hz in this study, which is the default value on the sensor-changing event within the smart phone.

Two data sets: 3D acceleration (*t, Ax, Ay, Az*) and 3D orientation angles (*t, θx , θy, θz*) were obtained at the same time by using the accelerometer and orientation sensor embedded in the smart phone. Subsequently, the two data sets were integrated as one data set (*t, Ax, Ay, Az, θx, θy, θz*), and used for the evaluation of the posture classification and fall detection algorithms. Additionally, the GPS and Wi-Fi signals were collected and used for outdoor and indoor localization. The recorded data and analyzed results were saved in the phone in text format in real-time.

C. *Existing Fall Detection Algorithms*

Falls can occur in various situations, during walking, during standing, or even during sitting. Existing algorithms for fall detection can be grouped into three categories:

- Comparison with pre-defined thresholds [6]; a large acceleration change infers a fall. This approach is suitable when an impact shock occurs, and suffers false positives from similar events such as sitting down heavily.
- Assumes that falls end with a posture of lying horizontally [11]. This assumption does not work when the user results in the sitting position after a fall.
- Machine learning techniques based on a trained model [12]. These algorithms consume significant computational time for the model training. Additionally, the various fall activity situations are particularly difficult to predict by such supervised machine learning algorithms.

In order to adapt to the various fall situations, understanding the principles of the data measuring devices is helpful for the purposes of algorithm design.

D. *Principles for Accelerometer and Orientation Sensor*

1) *Accelerometer*

We know that an accelerometer is a device that can measure the static acceleration due to gravity, and dynamic acceleration resulting from motion, shock, or vibration [13].

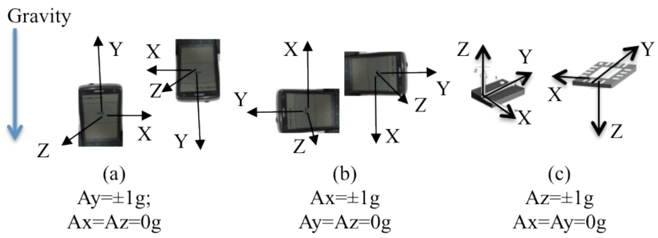

Figure 2. Output of the stationary acceleration vs. orientation to gravity. (a) Ay=±1g when the phone is vertical; (b) Ax=±1g when the phone is horizontal; (c) Az=±1g when the phone's screen is parallelized with the earth's surface.

An accelerometer will measure a value of ±1g (unit of gravity acceleration, which is $9.81m/s^2$) in the upward or downward direction if it remains stationary relative to the earth's surface. If the accelerometer is embedded in a smart phone, six 3D coordinate systems are apparent (vertical axis is X, Y or Z in upward or downward directions) according to the phone's orientations, as shown in Fig.2 (a), (b) and (c).

Fig.2 illustrates that the 3D stationary acceleration along the vertical-axis value will be ±9.81m/s^2, and along the other two axes will be 0 in theory. In the real world, the stationary acceleration (Ax, Ay, Az) during the motionless period of time (t_{ml}), must conform to equation (1).

$$\left|A_{vert}(t_{ml})\right| \equiv Max\left(\left|A_x\right|,\left|A_y\right|,\left|A_z\right|\right) \approx g \qquad (1)$$

The vertical-axis is always the axis, which has the maximum value among (|Ax|, |Ay|, |Az|) and is approximately equal to the gravity acceleration. The vertical-axis may be converted if the phone's orientation changes, so some special postures (such as lying) can be inferred according to the vertical-axis shifts between (Ax, Ay, Az) as shown in Fig. 3.

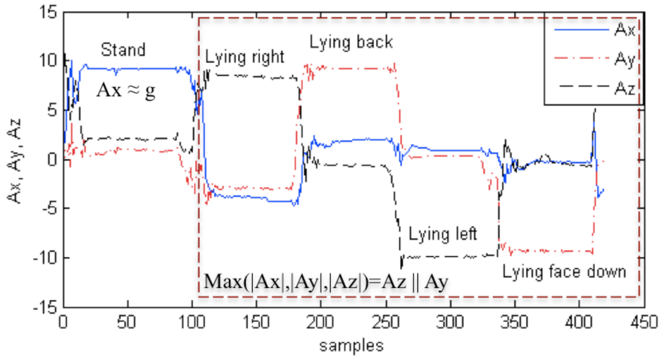

Figure 3. The relationship between the body postures and maximum value of (|Ax|, |Ay|, |Az|).

Fig.3 illustrates that if the body posture is upright such as stand, sit or walk, then the maximum absolute acceleration is Ax, and the X-axis is vertical; otherwise if the body posture is lying right (Lyi-R), back (Lyi-B), left (Lyi-L) and lying face down (Lyi-Fd), then the maximum value of *(|Ax|, |Ay|, |Az|)* is Ay or Az, so the vertical-axis will be Y or Z axis.

2) Orientation Sensor

The phone's orientation (or position relative to the magnetic north) can be monitored using the orientation sensor, which provides 3D rotation angles along the three axes (pitch, roll, azimuth), denoted as (θx ,θy, θz), as shown in Fig.4 (a).

- Pitch (θx) measures degrees of rotation around the X-axis; the range of values is -180° to 180°, with positive values when the positive z-axis moves toward the positive Y-axis. It is around 0° when the X-axis is vertical; it is around ±90° when the Y-axis is vertical; it is around ±180° when the top of the screen points towards the ground.
- Roll (θy) measures degrees of rotation around the Y axis, -90°<=θy <=90°, with positive values when the positive z-axis moves towards the positive X-axis. It is around 0° when the Y-axis is vertical; it is around ±90° when the X-axis is vertical.
- Azimuth (θz) measures degrees of rotation around the Z axis, 0°<=θz<=360°. It is used to detect the compass direction. Such as θz =0° or 360°, North; θz =180°, South; θz =90°, East; θz =270°, West.

According to the definition of the (θ_X ,θ_Y, θ_Z) above, the three angles will vary according to the specific body postures as shown in Fig. 4 (b) ~ (f).

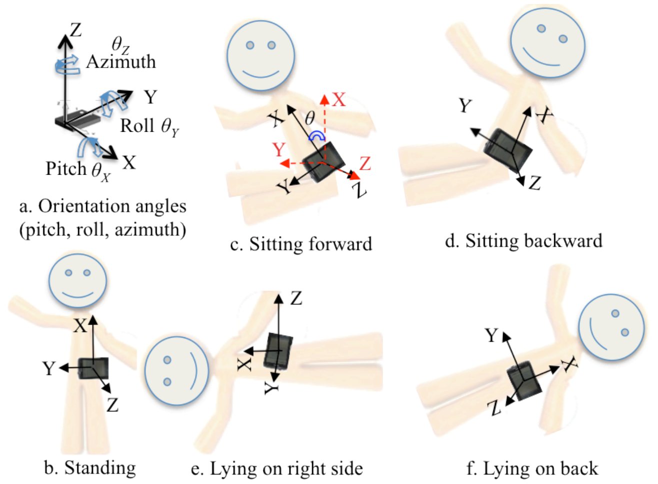

Figure 4. The orientation of the sensor coordinate system varies according to the body postures. (a) The orientation angles around 3-axis; (b) ~ (f) the vertical axis is different when the body posture is upright, tilted and lying.

Case1: When the body is upright as shown in Fig.4 (b), the x-axis is vertical, then the $|\theta_X|$ must be around 0°, and $|\theta_Y|$ must be around 90°, in theory.

Case2: When the body is tilted forward or backward as shown in Fig.4 (c) and (d), the x-axis and y-axis is rotated in a counter-clockwise or clockwise direction, then the $|\theta_Y|$ must be less than 90°, and $|\theta_X|$ must be between 0° and 90° in theory.

Case3: When the body is lying to the right as shown in Fig.4 (e), the z-axis is approximately vertical and the top of the phone screen points towards the sky, then the $|\theta_X|$ and $|\theta_Y|$ must all be around 0° in theory.

Case4: When the body is lying back or face down as shown in Fig.4 (f), the y-axis is approximately vertical, then the $|\theta_X|$ must be around 90°, and $|\theta_Y|$ must be around 0° in theory.

Case5: When the body is tilted left, the top of the screen points toward the ground, then the $|\theta_X|$ must be around 180°. When the body is tilted right, the top of the screen points toward the sky, the $|\theta_X|$ must be around 0°, and $|\theta_Y|$ must be less than 90°, in theory.

Therefore, by combining the principles of acceleration and orientation angles it is possible to recognize the lying, tilted and upright postures, which will be discussed in the postures classification Section.

E. Posture Transition Analysis for Falls Detection

The various falls can be categorized into two cases:

1) Hard falls, defined as hitting the ground or an obstacle heavily with the participant unexpected ending with a *lying or sitting tilted posture. In this case, a big impact force will lead to a large acceleration change.*

2) Soft falls, defined as unintended lying or sitting tilted on a lower level (such as the ground or sofa); descent is slow and gent. In this case, there is no big impact force to cause large acceleration change.

The same endpoint for the two types of falls is an *unintended* lying or sitting tilted posture; the difference can be inferred by the change of acceleration. So if a fall detection algorithm was only based on acceleration analysis, it is not possible to detect the soft falls; also if an algorithm was only based on the lying or sitting tilted postures to detect falls, it will cause many false positives due to normal lying or sitting activities such as lying on the bed for sleeping, sitting tilted on the chair for reading.

Based on the hard falls and soft falls definition, we developed a fall detection algorithm to detect falls in two steps: 1) recognize the lying or sitting tilted postures from daily activities; 2) analyze whether the current lying or sitting tilted postures are normal (intended) or abnormal (unintended).

1. Postures classification

The motion and motionless postures are classified using a hierarchal rule-based algorithm. First, a motionless rule (R_{ML}) was used to separate the motion and motionless postures in two arrays; next a lying rule (R_{Lyi}) was used to distinguish the lying postures from other motionless postures such as standing and sitting; then a tilted rule (R_{Til}) was used to recognize the tilted postures from upright postures; finally, the motion postures were initially classified as a walk or posture transition (PT) according to the motion period of time. The posture classification procedure was shown in Fig. 5.

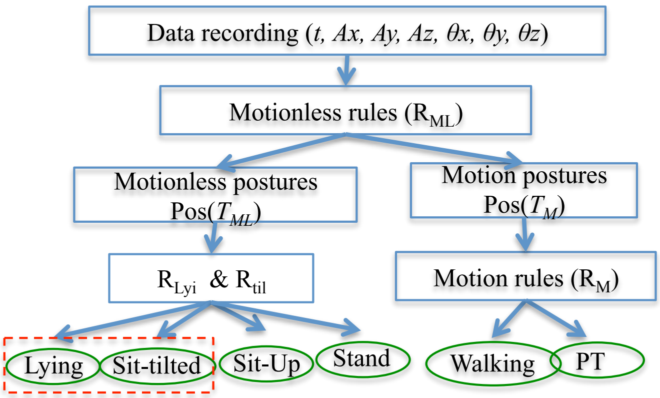

Figure 5. Flowchart of posture classification.

R_{ML}: consider a motionless period T_{ml} from t_m to t_l, the R_{ML} was defined as: the motionless period T_{ml} extends for more than a predefined period of motionless time (*mlp*) as expressed in (2); the change of acceleration (ΔAx) is less than an empirical threshold *th*1 as presented in (3).

$$R_{ML} = \begin{cases} \forall [t_i, t_l] \in T_{ml}; \quad T_{ml} \geq mlp & (2) \\ \Delta A_x = |A_x(t_{i+1}) - A_x(t_i)| \leq th1 & (3) \end{cases}$$

where the motionless is defined as no motion for at least 2 seconds (*mlp* = 2s), which provides appropriate details and reduces the posture fragments for long term daily activity monitoring; and *th1*=0.4m/s^2; these values were determined empirically, it can guarantee that the motionless activities can be detected.

R_{Lyi}: During a motionless period of time, if the maximum absolute value among (*Ax, Ay, Az*) is not *Ax*, and it approximately equal to g as expressed in (4) and (5), then the motionless posture must be lying. This lying rule is established based on the accelerometer principles.

$$R_{Lyi} = \begin{cases} A_{\max} = Max(|A_X|,|A_Y|,|A_Z|) \approx g & (4) \\ A_{\max} \neq A_X & (5) \end{cases}$$

R_{Til}: if ($|\theta_X|$ >= (0°+θ_{Cali}) or $|\theta_Y|$<=(90°−θ_{Cali}), then the motionless posture must be tilted. This tilted rule is established based on the orientation sensor principles.

where the practical value θ_{Cali} is used to calibrate the ideal value for θx and θy. Ideally, the θy is around ±90° and θx is around 0° when the X-axis is vertical, neverthless, it is difficult to guarantee that the belt-worn phone keeps ideally vertical when the body posture is upright (such as standing), so a practical value θ_{cali} = 20° is used to calibrate the ideal value for θx and θy respectively.

2. Falls Analysis

We know that the common features for all kinds of falls are that the body results in a lying or sit-tilted posture, however, not all lying or sit-tilted postures are falls. Based on the results of posture classification, the falls detection was implemented by analyzing whether the current lying and tilted sitting postures are normal or abnormal based on the posture transition and users' current position. The flowchart of fall analysis is shown in Fig.6. Details of falls analysis are described in step1 and step2.

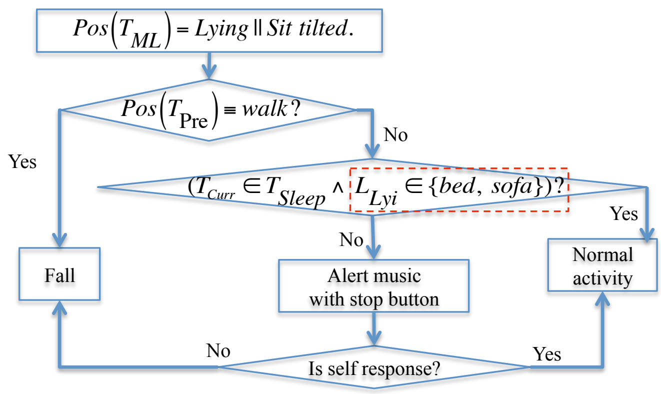

Figure 6. Flowchart of the fall analysis and determination. Notes: the location detection algorithms were not presented in this paper, since the limited pages.

Step1: If the lying or sit-tilted posture was detected at the motionless period of time, then the previous activity posture Pos(TPre) will be checked using backward reasoning. If

Pos(TPre)=Walk, thus the posture transition from walking to lying or sit-tilted suddenly is determined as abnormal, especially for the elderly, a fall alert should be triggered immidiatly.

Step2: If Pos(TPre) ≠ Walk, then check whether the lying or sit-tilted posture is at the right time and in the right place. If the current time Tcurr. is not within the prescheduled sleeping or nap period of time TSleep, or the lying position LLyi is not on the bed or sofa, then a possible fall is raised, so a music alert starts playing. Finally, a fall or a normal activity will be determined according to whether the user stops the alert music.

IV. EXPERIMENTS

The proposed fall detection algorithm was evaluated in real-time using a smart phone, at a home environment by three healthy subjects (2 male and 1 female; aged 23, 48 and 50). The interface of the system is shown in Fig.1 (e). The experimental results were validated against notes recorded by two people at the same time following the experiments. The notes were pre-designed as a table that included three items (posture name, start time and end time) for each of the serial activities. For safety purposes, a mat was put on the ground for the falls experiments.

Experiment 1: Various Falls

Each of the three subjects performed the following activities in random order and random period of time, which includes various falls such as hard falls from walk to lying/sit-tilted quickly on the ground, sofa, or bed, and soft falls from walk to lying/sit-tilted slowly on the ground, bed, or sofa.

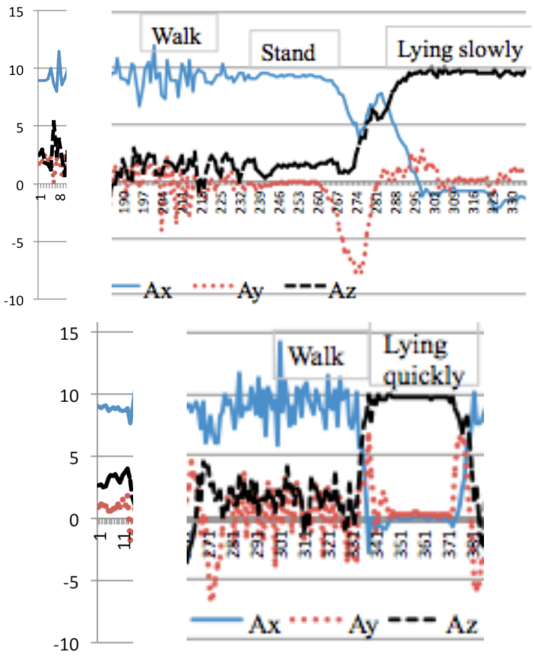

Figure 7. Comparison of lying slowly and lying quickly. The left side figure shows the part of acceleration signals from standing to lying slowly; right side fiture shows the part of acceleration signals from walk to lying suddenly.

1) From walking to lying right, back, left, and face down respectively, on the ground suddenly (quickly);
2) From walking to sitting leaning right, back, left and forward respectively, on the ground suddenly;
3) Repeat all activities in 1) and 2), however, the ground is changed to a bed or sofa;
4) From walking to standing, then from standing to lying and sit-tilted respectively, on the ground slowly.
5) From walking to standing, then from standing to lying on a bed or a sofa slowly.

Activities from walking to lying or sit-tilted suddenly are defined as abnormal posture transition, especially for elderly people. Falls should be detected in these cases, as shown in bottom of Fig.7. In step 4), although the posture transition from standing to lying or sit-tilted slowly is normal, however if the lying or sit-tilted posture is in a wrong place (ground), a possible fall alert music should be playing in this case, as shown in top of Fig.7. In step 5), the posture transition and lying position all are normal, hence the lying time will be the key element for the possible fall detection.

Experiment 2: Normal lying in two ways

The normal lying in two ways: sitting for more than 2 seconds and sitting for less than 2 seconds before they are lying on a bed or a sofa. Each of the three subjects undertook the following series of activities in random order and random period of time. Fig. 8 shows the part of acceleration signals collected from subject1.

walk → sit on a bed for more than 2s → *lying* on the bed → *get* up → *walk* → sit on the bed < 2s → lying on the bed → get up → *walk* → sit on a sofa >2s → *lying* on the sofa → get up → walk → sit on the sofa <2s → *lying* on the sofa .

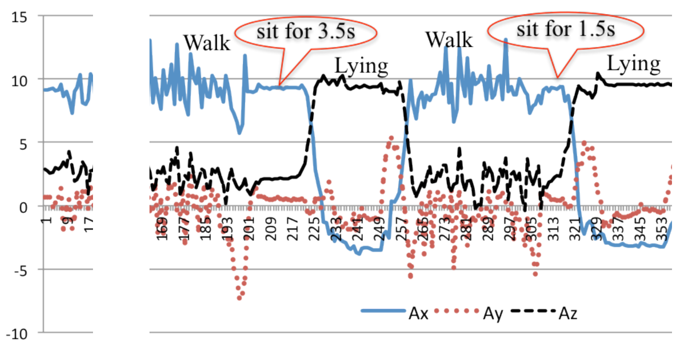

Figure 8. The part of acceleration signals collected from subject1, who did the normal lying in two ways.

In these experiments, there were 24 (=8×3) falls ending with lying (in this case, the acceleration changing is large); 24 falls ending with sitting tilted (in this case, the acceleration changing is small); 9 (=3×3) possible falls; and 12 (=4×3) normal lying or sit-tilted activities performed in total. The falls were distinguished using two algorithms ('*posture transition'* and '*thresholds'* described below) respectivley, the experimental results were evaluated in real-time according to the alert music and presented in Table I.

Algorithm1(posture transition): falls were detected based on the posture transition analysis and current position, as proposed on this paper.

Algorighm2(thresholds): falls were detected only using acceleration changing with pre-defined threshold, as described on our previous work [14].

Table I has demonstrated that the *algorithm1* can improve falls detection accuracy significantly in both aspects: true positives (real falls) and true negatives (non-falls) compared to *algorithm2*. *Algorithm1* was able to correctly detect 48/48 of falls ending with lying or sit-tilted, and 6/12 of non-fall (normal lying). It is limited for the normal lying analysis when the sitting period of time is less than 2 seconds before the lying. Additionally, it can trigger the alert music with a stop butter for the 9 possible falls, and determin whether it is a real fall occurred according to the user's response (whether he/she stops the alert music).

Algorithm2(theshold) was able to detect the 24/24 of falls ending with lying correctly. It recognized 0/24 of falls ending with sit-tilted and 0/12 of normal lying (non-fall), since the normal lying posture also causes a large acceleration changing. For the 9 possible falls, it only can detect the falls correctely when users were lying on the ground.

TABLE I. COMPARISON OF EXPERIMENTAL RESULTS BETWEEN TWO ALGORITHMS

Algorithms	Falls		Normal Lying	Possible Falls	Total (Accuracy)
	Lying	*Sit-tilted*			
Algorithm1	24/24	24/24	6/12	9/9	63/69
Algorithm2	24/24	0/24	0/12	3/9	27/69

A limitation for *algorithm1* proposed in this paper is caused by the motionless definition. In this study, the motionless postures were defined as no motion for at least 2 seconds. In this case, if the sitting period of time is less than 2 seconds before the lying (such as 1.5 seconds as shown in Fig.8), then this sitting posture will be ignored based on the motionless rule. Thus the normal posture transition from sitting to lying was analyzed as from walk to lying (wrong posture transition order), hence it was detected as a fall.

V. CONCLUSION AND FUTURE WORK

The main contributions of this paper are: 1) the posture classification algorithms were developed based on the principles of accelerometer and orientation sensors, it is reliable for different subjects and different situations, since it is not only based on empirical thresholds or subject-based training models; 2) the fall detection algorithm was designed based on the posture transition analysis and current position, it can correctly detect various falls efficiently (real-time within a smart phone) and also avoid the most false positives and false negatives. Experiments were performed in various situations such as hard falls on the ground, soft falls on the bed, falls ending with a lying or sit-tilted posture, in addition to the normal lying, at a real home environment.

More activity postures and falls situations such as up/down stairs, cycling, and driving and running will be addressed in the future work. An open question may be raised from this study: for the motionless definition, whether the 2 seconds should be as a necessary condition? According to our experience, this condition can reduce the posture fragments for a long term daily activity monitioring, since the short time (less than 2 seconds) motionless period will be ignored during the motion period.

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